Banks are eager to retain as many active customers as possible. Naturally they are curious to know whether their client base needs are met or whether their clients plan to leave the company. If the bank suspects that their client would potentially lean toward another company, the bank can take measures to convince the client to stay (targeted marketing campaign, more personal attitude etc.).

Aim of this notebook is to find the most accurate and precise model to predict, which clients (test data) will stay and which are hesitant and might plan to leave the company. We are using dataset of bank clients (10000 rows) with attributes specified below. Let's jump right into it! □

Dataset has following attributes:

Rownumber: Unique ID for every row

CustomerID: Unique ID for every client

Surname: Client's surname

CreditScore: Client's credit score

Geography: Country of client's origin

Gender: Client's gender

Age: Client's age

Tenure: Number of years for which the client has been with the bank

Balance: Client's balance on account

NumOfProducts: Number of client's products

HasCrCard: Flag whether client has credit card or not

IsActiveMember: Flag whether client is active member of bank or not

EstimatedSalary: Client's annual estimated salary in euros

Exited: Target variable, flag, whether client left the bank or not

Import the Libraries

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
```

```

```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.
```

Import the dataset

```
df1=pd.read_csv('/content/drive/MyDrive/Colab_Notebooks/DL/Churn_Modelling.csv')
```

Checking the 1st 5 Rows in our dataset

```
df1.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	I
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	8
2	3	15619304	Onio	502	France	Female	42	8	15
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	12

Explanatory Data Analysis(EDA)

Firstly Drops RowNumber,CustomerId,Surname these columns. These may not help in model building

```
df1.drop(columns = ['RowNumber','CustomerId','Surname'], inplace= True )
```

```
df1.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCar
0	619	France	Female	42	2	0.00	1	
1	608	Spain	Female	41	1	83807.86	1	
2	502	France	Female	42	8	159660.80	3	
3	699	France	Female	39	1	0.00	2	
4	850	Spain	Female	43	2	125510.82	1	

```
df1.isnull().sum()
```

```
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

```
df1.describe()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	Has
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	1000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	
std	96.653299	10.487806	2.892174	62397.405202	0.581654	
min	350.000000	18.000000	0.000000	0.000000	1.000000	
25%	584.000000	32.000000	3.000000	0.000000	1.000000	
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	
max	850.000000	92.000000	10.000000	250898.090000	4.000000	

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
```

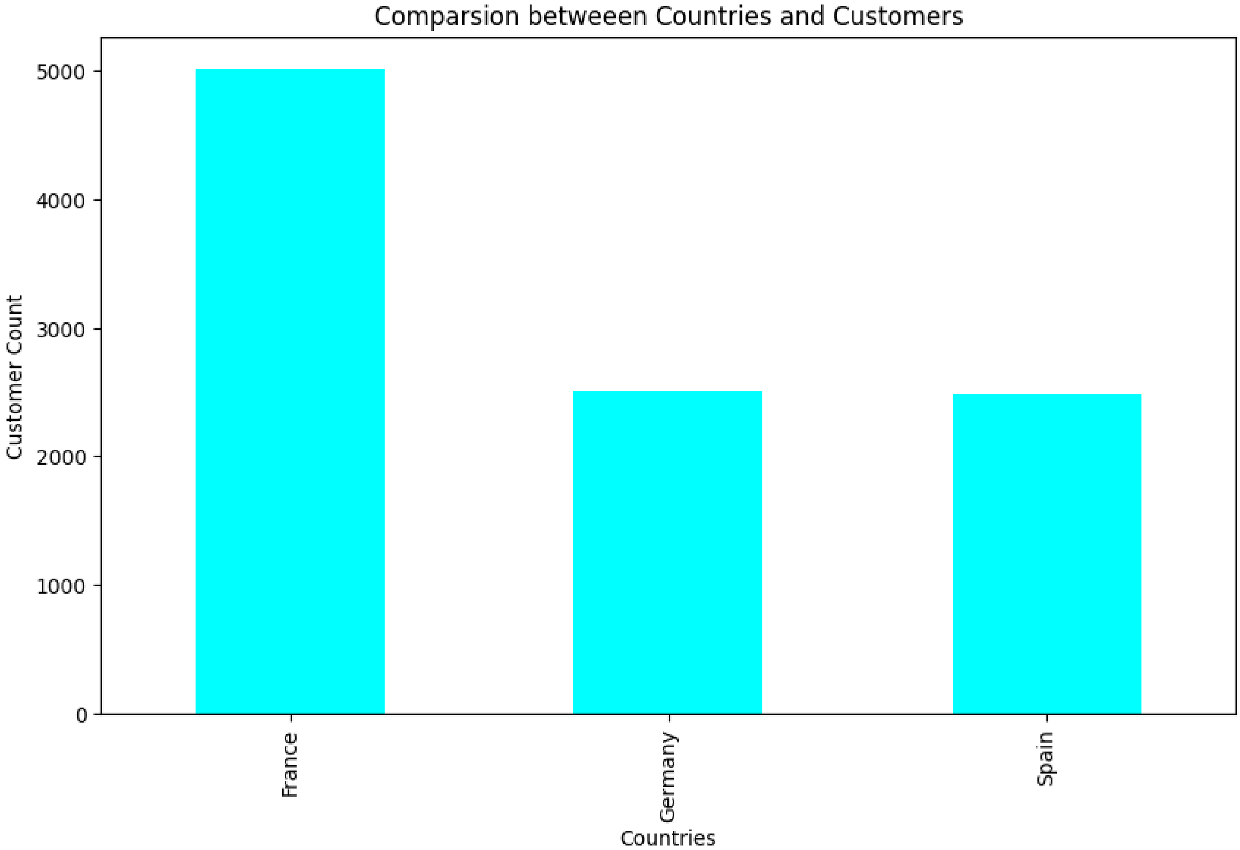
```
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

```
df1['Geography'].value_counts()
```

```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

```
plt.figure(figsize=(10, 6))
df1['Geography'].value_counts().plot(kind='bar', color = 'cyan')
plt.xlabel('Countries')
plt.ylabel('Customer Count')
plt.title("Comparsion betweeen Countries and Customers")
```

```
Text(0.5, 1.0, 'Comparsion betweeen Countries and Customers')
```



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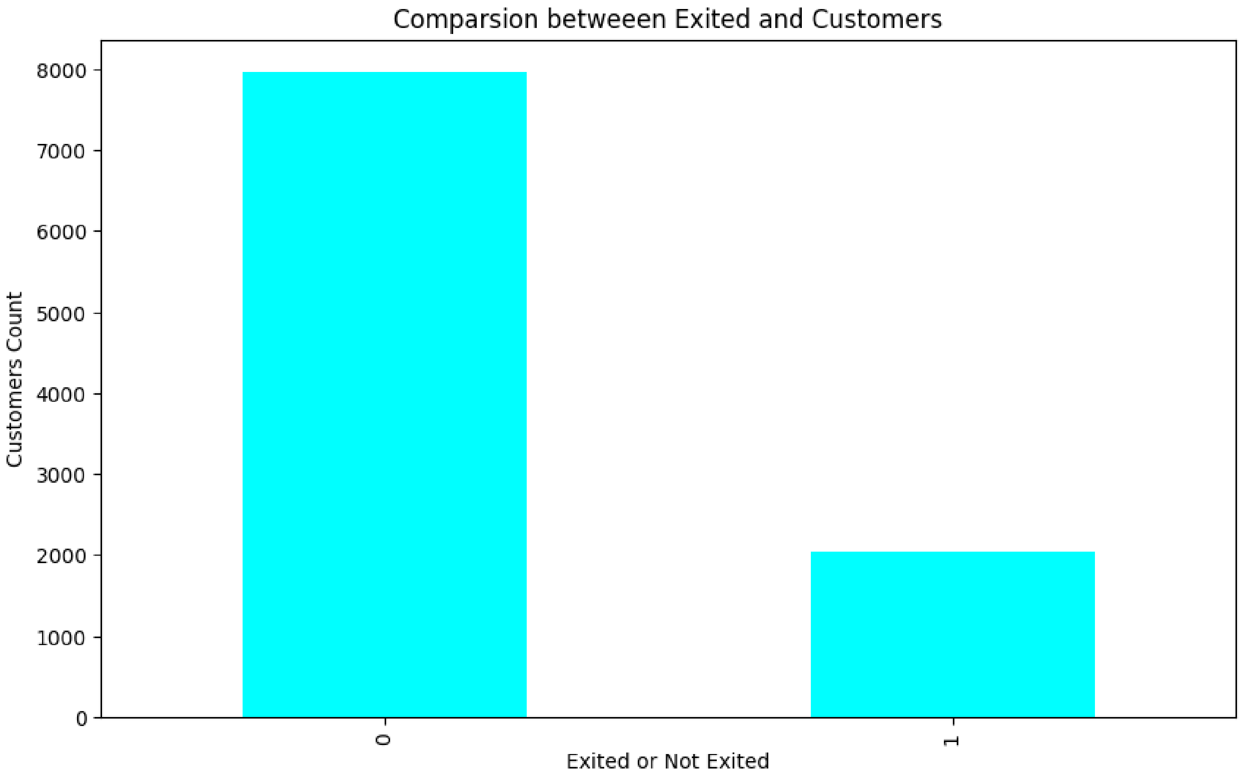
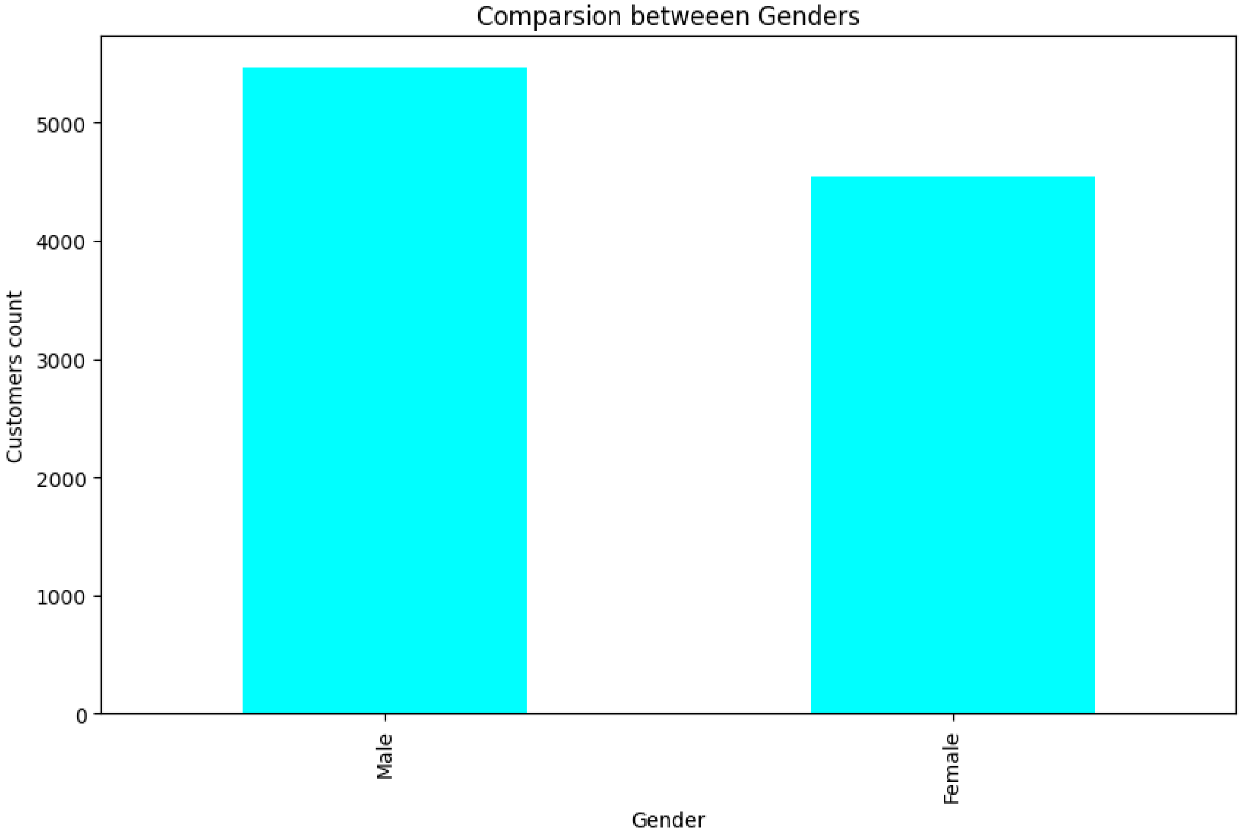
```
plt.figure(figsize=(10, 6))
df1['Exited'].value_counts().plot(kind='bar', color = 'cyan')
plt.xlabel('Exited or Not Exited')
plt.ylabel('Customers Count')
plt.title("Comparsion betweeen Exited and Customers")
```

```
Text(0.5, 1.0, 'Comparsion betweeen Exited and Customers')
```



```
plt.figure(figsize=(10, 6))
df1['Gender'].value_counts().plot(kind='bar', color = 'cyan')
plt.xlabel('Gender')
plt.ylabel('Customers count')
plt.title("Comparsion betweeen Genders")
```

```
Text(0.5, 1.0, 'Comparsion betweeen Genders')
```



Encoding the Categorical data

```
df1= pd.get_dummies(df1, columns= ['Geography', 'Gender'], drop_first=True)
```

get_dummies function : For converting categorical columns into numerical columns

```
X=df1.drop(columns=['Exited'])
y=df1['Exited']
```

Now Split the dataset into train test split using sklearn lib

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size= 0.30, random_state=
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
```

```
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
```

Building our Model using Artificial Neural Network (ANN)

Import the Libraries

```
import tensorflow
from tensorflow import keras
from tensorflow.keras import Sequential # used for init our ANN model
from tensorflow.keras.layers import Dense # used for different layer structure
```

Initialize our ANN model

```
# initializing the ANN model
identifier=Sequential()
```

Adding the input layer and first hidden layer

```
identifier.add(Dense(6,activation='relu',input_dim=11))
identifier.add(Dense(6,activation='relu'))
identifier.add(Dense(1,activation='sigmoid'))
```

```
identifier.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_3 (Dense)             (None, 6)                 72
```

```
 dense_4 (Dense)           (None, 6)                 42

 dense_5 (Dense)           (None, 1)                 7

=================================================================
Total params: 121
Trainable params: 121
Non-trainable params: 0
_________________________________________________________________
```

```
1 identifier.compile(optimizer='Adam',loss='binary_crossentropy',metrics=['accuracy'])
```

```
1 track = identifier.fit(X_train,y_train,batch_size=10,epochs=100,verbose=1,validation_sp
```

```
Epoch 1/100
525/525 [==============================] - 3s 3ms/step - loss: 0.5172 - accuracy:
Epoch 2/100
525/525 [==============================] - 1s 2ms/step - loss: 0.4540 - accuracy:
Epoch 3/100
525/525 [==============================] - 1s 2ms/step - loss: 0.4307 - accuracy:
Epoch 4/100
525/525 [==============================] - 1s 2ms/step - loss: 0.4196 - accuracy:
Epoch 5/100
525/525 [==============================] - 1s 2ms/step - loss: 0.4113 - accuracy:
Epoch 6/100
525/525 [==============================] - 1s 2ms/step - loss: 0.4001 - accuracy:
Epoch 7/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3854 - accuracy:
Epoch 8/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3671 - accuracy:
Epoch 9/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3557 - accuracy:
Epoch 10/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3489 - accuracy:
Epoch 11/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3448 - accuracy:
Epoch 12/100
525/525 [==============================] - 2s 3ms/step - loss: 0.3420 - accuracy:
Epoch 13/100
525/525 [==============================] - 2s 3ms/step - loss: 0.3404 - accuracy:
Epoch 14/100
525/525 [==============================] - 2s 3ms/step - loss: 0.3388 - accuracy:
Epoch 15/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3378 - accuracy:
Epoch 16/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3366 - accuracy:
Epoch 17/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3362 - accuracy:
Epoch 18/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3352 - accuracy:
Epoch 19/100
525/525 [==============================] - 2s 3ms/step - loss: 0.3347 - accuracy:
Epoch 20/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3347 - accuracy:
Epoch 21/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3339 - accuracy:
Epoch 22/100
525/525 [==============================] - 2s 3ms/step - loss: 0.3334 - accuracy:
```

```
Epoch 23/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3327 - accuracy:
Epoch 24/100
525/525 [==============================] - 1s 3ms/step - loss: 0.3320 - accuracy:
Epoch 25/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3320 - accuracy:
Epoch 26/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3313 - accuracy:
Epoch 27/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3315 - accuracy:
Epoch 28/100
525/525 [==============================] - 1s 2ms/step - loss: 0.3309 - accuracy:
```

Prediction and Accuracy Result

```
# predicting the test set result
y_pred = identifier.predict(X_test)
y_pred = (y_pred>0.5)
y_pred

```

```
94/94 [==============================] - 0s 2ms/step
array([[False],
       [False],
       [ True],
       ...,
       [False],
       [False],
       [False]])
```

Confusion metrics

```
# Confusion Metric
from sklearn.metrics import confusion_matrix
confusion_metric = confusion_matrix(y_test, y_pred)
confusion_metric
```

```
array([[2271,  110],
       [ 320,  299]])
```

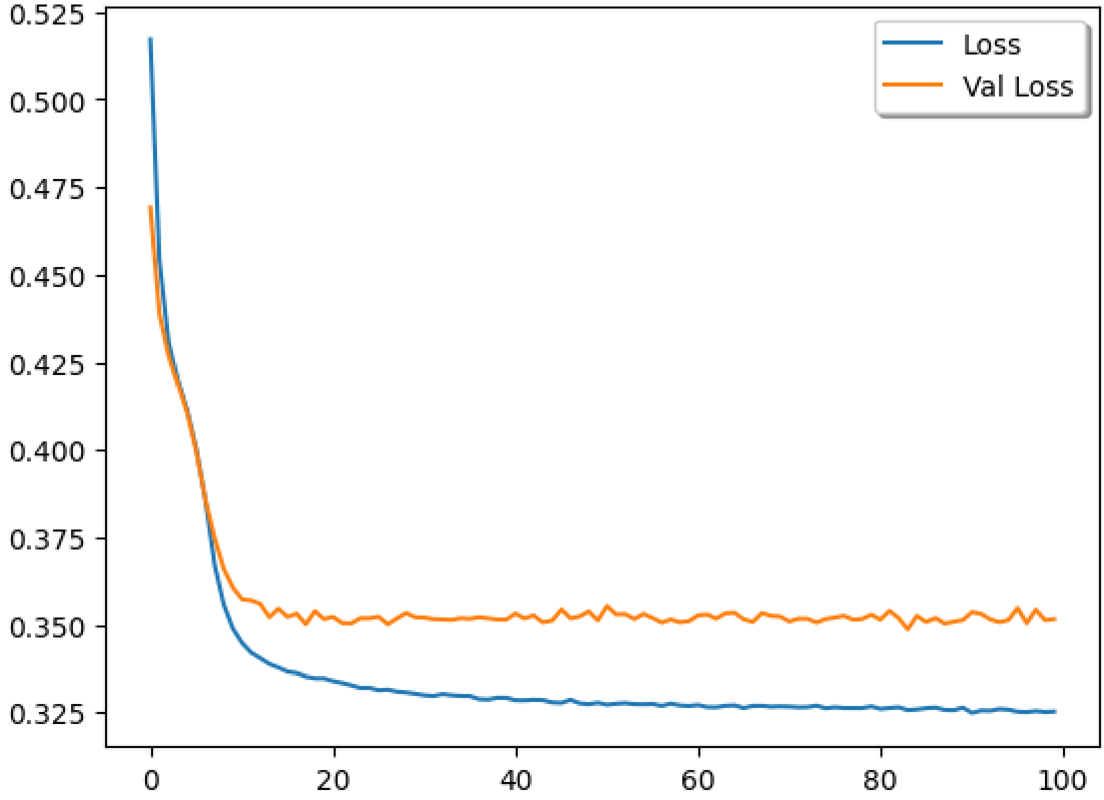
Score

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test,y_pred)
```

```
0.8566666666666667
```

```
plt.plot(track.history['loss'])
plt.plot(track.history['val_loss'])
plt.legend(('Loss', 'Val Loss'),
           loc='upper right', shadow=True)
```

```
<matplotlib.legend.Legend at 0x7fb202cd6340>
```



```
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```
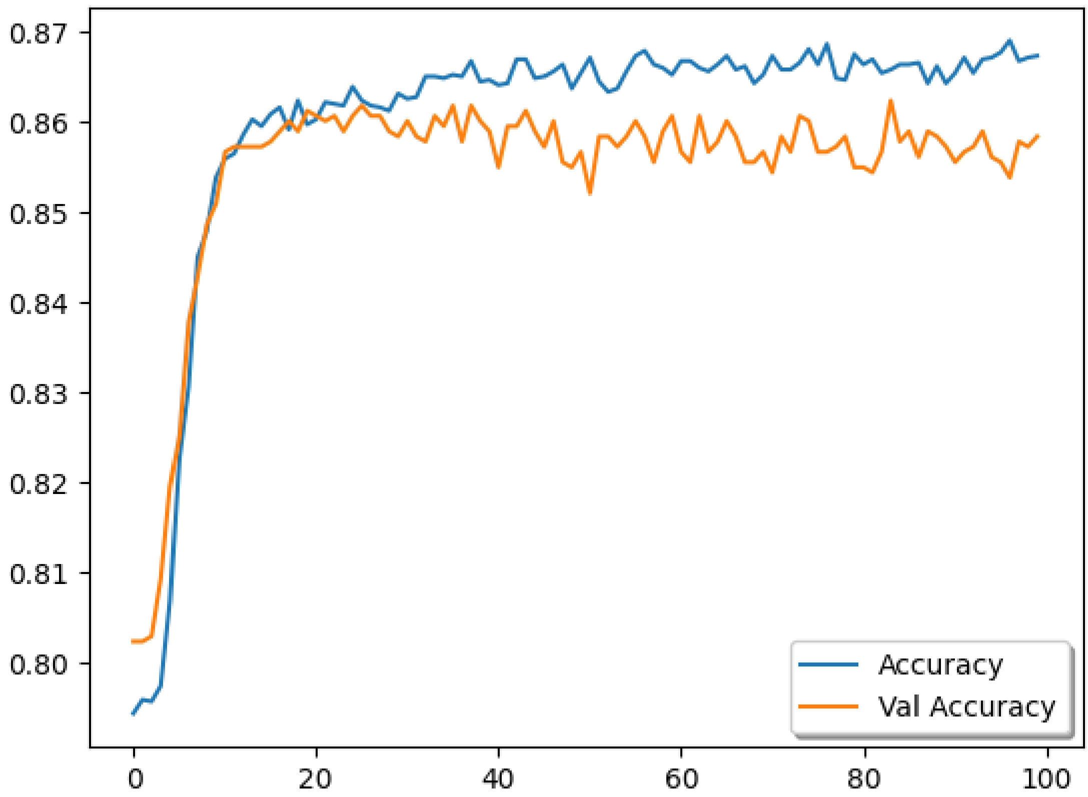

Graph between loss and val_loss

```python
plt.plot(track.history['accuracy'], label='test')

plt.plot(track.history['val_accuracy'])
plt.legend(('Accuracy', 'Val Accuracy'),
           loc='lower right', shadow=True)
```

```
<matplotlib.legend.Legend at 0x7fb202aed700>
```



Double-click (or enter) to edit

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